Performance Evaluation of Medical Device Suppliers with Fuzzy DEA Technique

Mehtap Dursun, Zeynep Sener, and Michele Cedolin

***Abstract*—In order to achieve customer satisfaction in healthcare industry, the selection process of the right medical device suppliers among a number of alternatives is very critical. In this study, performance supplier alternatives' performances are evaluated using fuzzy data envelopment analysis technique. The subjective judgments of decision makers are expressed by means of linguistic variables. The proposed fuzzy group decision making approach is illustrated through a medical supplier selection problem.**

***Index Terms*—Fuzzy data envelopment analysis, performance assessment, medical supplier evaluation**

I. Introduction

Supplier selection, which takes place in the context of supply chain management, is considered as a strategic decision making problem that help managers remain competitive [1]. Suppliers are considered as crucial part of any value chain network since they may improve the profitability, competition capability and customer satisfaction [2]. Therefore, suppliers' performances affect directly cost effectiveness, delivery time and service quality of a supply chain [3].

Growing market competition and rapid changes in customer choices lead firms to collaborate with efficient suppliers for achieving the competitive advantage [2]. Supplier selection decisions are quite sophisticated since various criteria must be taken into account in decision making process [1].

Supplier selection problem may be employed in both manufacturing and service sectors. Increasing health expenses, competition and improved quality in health sector motivate hospitals to allocate their resources efficiently [1]. Hence, hospitals may face with decreased quality, increased cost, delivery time problems and disruption in whole system due to the lack of medical device supplier selection process. Selecting the right medical device supplier enhances the competitive advantage of the hospitals.

This paper proposes to employ data envelopment analysis (DEA) technique for assessing medical suppliers' performances. Linguistic variables and fuzzy numbers are used to quantify the impreciseness inherent in the supplier selection process.

The original data envelopment analysis model, also called as the CCR model, proposed by Charnes et al.[4], calculates the relative efficiency of a decision making unit (DMU) by maximizing the ratio of its total weighted outputs to its total weighted inputs with a constraint that the output to input ratio of every DMU is less than or equal to unity. Throughout the literature, several approaches such as weight restriction and cross-efficiency analysis have been developed in order to handle the unrealistic weight distribution and improve the discriminating power of DEA [5]-[6]. Besides, minsum and minimax efficiency models do not give favorable consideration to the DMU under evaluation unlike the traditional DEA model [7]. Minimax efficiency is to minimize maximum deviation from efficiency whereas minsum efficiency minimizes the total deviation from efficiency [8].

Albeit the conventional DEA models are limited for dealing technology, supplier or health-care service systems evaluation and selection problems, the observed data set may provide vague and imprecise knowledge about the generating process [9]. Then use of the fuzzy measures and fuzzy mathematical programs in the DEA models is unavoidable, which are obtained from the experts, generally by linguistic terms, and then denoted as fuzzy numbers [10]-[11]. Fuzzy DEA, is an extension of DEA which incorporates imprecision in DEA. There are several approaches in fuzzy DEA literature, such as tolerance approach [9], the α-cut approach [12]-[13] fuzzy ranking approach and the possibility approach [14]-[16].

In this study, the model proposed by Karsak [17] is employed to deal with the explained case-study problem. The selected framework, deal the problem with two perspectives, namely optimistically and pessimistically.

This paper presents a fuzzy group decision making approach based on fuzzy DEA to identify the most appropriate medical device supplier. The rest of the study is organized as follows. Section II outlines fuzzy data envelopment analysis method. The subsequent section illustrates the proposed methodology via a numerical example. Final section delineates the conclusions and future research directions.

II. FUZZY DATA ENVELOPMENT ANALYSIS TECHNIQUE

The preliminary model proposed by Charnes et al. [4], obtains the efficiency score as the maximum of a ratio weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity. Their model is as follows:

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$$\max E_{j_0} = \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}$$

subject to (1)

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad \forall j,$$

$$u_r, v_i \geq \varepsilon, \quad \forall r, i.$$

where E_{J_0} is the efficiency score of the evaluated DMU, u_r is the weight assigned to output *r*, v_i is the weight assigned to input i, y_{rj} is the quantity of output *r* generated and x_{ij} is the amount of input *i* consumed by DMU *j*, respectively, and ε is a small positive scalar.

In this part of the study, the employed DEA model which incorporates both exact and imprecise data is presented. The model proposed by Karsak [17] is simplified due to the non-existence of ordinal data in the inputs or outputs, and subsets of ordinal outputs and ordinal inputs are eliminated from the model for providing a clear understanding.

Let $\tilde{x}_{ij} = (x_{ija}, x_{ijb}, x_{ijc}),\ for\ 0 \leq x_{ija} \leq x_{ijb} \leq x_{ijc}$, present the fuzzy input *i* employed by the *j*th DMU, and $\tilde{y}_{rj} = (y_{rja}, y_{rjb}, y_{rjc}),\ for\ 0 \leq y_{rja} \leq y_{rjb} \leq y_{rjc}$, denote the fuzzy output *r* produced by the *j*th DMU. Let

$$(x_{ij})_\alpha^L = x_{ija} + \alpha_i (x_{ijb} - x_{ija}), \alpha_i \in [0,1], \quad (2)$$

$$(x_{ij})_\alpha^U = x_{ijc} - \alpha_i (x_{ijc} - x_{ijb}), \alpha_i \in [0,1], \quad (3)$$

$$(y_{rj})_\alpha^L = y_{rja} + \alpha_r (y_{rjb} - y_{rja}), \alpha_r \in [0,1], \quad (4)$$

$$(y_{rj})_\alpha^U = y_{rjc} - \alpha_r (y_{rjc} - y_{rjb}), \alpha_r \in [0,1]. \quad (5)$$

Where $(x_{ij})_\alpha^L$ and $(x_{ij})_\alpha^U$ denote the lower and upper bounds of the α-cut of the membership function of $\tilde{x}_{ij}$, and similarly, $(y_{rj})_\alpha^L$ and $(y_{rj})_\alpha^U$ present the lower and upper bounds of the α-cut of the membership function of $\tilde{y}_{rj}$, respectively.

Let $w_i = v_i \alpha_i$, where $0 \leq w_i \leq v_i$.
Then, $\sum_i v_i (x_{ij})_\alpha^L$ and $\sum_i v_i (x_{ij})_\alpha^U$ can be presented as

$$\sum_i v_i (x_{ij})_\alpha^L = \sum_i v_i \left[x_{ija} + \alpha_i (x_{ijb} - x_{ija})\right] = \sum_i v_i x_{ija} + w_i (x_{ijb} - x_{ija}), \quad (6)$$

$$\sum_i v_i (x_{ij})_\alpha^U = \sum_i v_i \left[x_{ijc} - \alpha_i (x_{ijc} - x_{ijb})\right] = \sum_i v_i x_{ijc} - w_i (x_{ijc} - x_{ijb}). \quad (7)$$

Likewise, let $\mu_r = u_r \alpha_r$, where $0 \leq \mu_r \leq u_r$. Then, $\sum_r u_r (y_{rj})_\alpha^L$ and $\sum_r u_r (y_{rj})_\alpha^U$ can be represented respectively as

$$\sum_r u_r (y_{rj})_\alpha^L = \sum_r u_r \left[y_{rja} + \alpha_r (y_{rjb} - y_{rja})\right] = \sum_r u_r y_{rja} + \mu_r (y_{rjb} - y_{rja}) \quad (8)$$

$$\sum_r u_r (y_{rj})_\alpha^U = \sum_r u_r \left[y_{rjc} + \alpha_r (y_{rjc} - y_{rjb})\right] = \sum_r u_r y_{rjc} + \mu_r (y_{rjc} - y_{rjb}). \quad (9)$$

Let $(E_{J_0})^U$ and $(E_{J_0})^L$ denote the upper and lower bounds of the α-cut of the membership function of the efficiency score for the evaluated DMU (j_0). Employing the replacements given above, the general optimistic scenario DEA model incorporating crisp and fuzzy data can be written as

$$\max (E_{J_0})^U = \sum_{r \in C_R} u_r y_{rj_0} + \sum_{r \in F_R} u_r y_{rj_0 c} - \mu_r (y_{rj_0 c} - y_{rj_0 b})$$

subject to (10)

$$\sum_{i \in C_I} v_i x_{ij_0} + \sum_{i \in F_I} v_i x_{ij_0 a} + w_i (x_{ij_0 b} - x_{ij_0 a}) = 1$$

$$\sum_{r \in C_R} u_r y_{rj_0} + \sum_{r \in F_R} u_r y_{rj_0 c} - \mu_r (y_{rj_0 c} - y_{rj_0 b}) - \sum_{i \in C_I} v_i x_{ij_0} - \sum_{i \in F_I} v_i x_{ij_0 a} + w_i (x_{ij_0 b} - x_{ij_0 a}) \leq 0$$

$$\sum_{r \in C_R} u_r y_{rj} + \sum_{r \in F_R} u_r y_{rja} + \mu_r (y_{rjb} - y_{rja}) - \sum_{i \in C_I} v_i x_{ij} - \sum_{i \in F_I} v_i x_{ijc} - w_i (x_{ijc} - x_{ijb}) \leq 0 \quad j = 1,2...,n;\ j \neq j_0$$

$$\mu_r - u_r \leq 0, r \in F_R$$
$$w_i - v_i \leq 0, i \in F_I$$
$$\mu_r \geq 0, r \in F_R$$
$$w_i \geq 0, i \in F_I$$
$$u_r \geq \varepsilon \geq 0, r \in C_R, r \in F_R$$
$$v_i \geq \varepsilon \geq 0, i \in C_I, i \in F_I$$

where F_R and F_I respectively represent the subset of fuzzy outputs $(F_R \subseteq R)$ and the subset of fuzzy inputs $(F_I \subseteq I)$, where *R* denotes the set of outputs $(C_R \cup F_R = R)$ and *I* represents the set of inputs $(C_I \cup F_I = I)$. Similarly, the

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general pessimistic scenario DEA model incorporating crisp and fuzzy data can be written as

$$\max(E_{J_0})^L = \sum_{r\in C_R} u_r y_{rj_0} + \sum_{r\in F_R} u_r y_{rja} + \mu_r (y_{rj_0 b} - y_{rj_0 a})$$

subject to (11)

$$\sum_{i\in C_I} v_i x_{ij_0} + \sum_{i\in F_I} v_i x_{ij_0 c} + w_i (x_{ij_0 c} - x_{ij_0 b}) = 1$$

$$\sum_{r\in C_R} u_r y_{rj_0} + \sum_{r\in F_R} u_r y_{rj_0 a} + \mu_r (y_{rj_0 b} - y_{rj_0 a}) - \sum_{i\in C_I} v_i x_{ij_0} - \sum_{i\in F_I} v_i x_{ij_0 c} - w_i (x_{ij_0 c} - x_{ij_0 b}) \le 0$$

$$\sum_{r\in C_R} u_r y_{rj} + \sum_{r\in F_R} u_r y_{rjc} - \mu_r (y_{rjc} - y_{rjb}) - \sum_{i\in C_I} v_i x_{ij} - \sum_{i\in F_I} v_i x_{ija} + w_i (x_{ijb} - x_{ija}) \le 0 \quad j = 1,2...,n;\ j \ne j_0$$

$$\mu_r - u_r \le 0, r \in F_R$$

$$w_i - v_i \le 0, i \in F_I$$

$$\mu_r \ge 0, r \in F_R$$

$$w_i \ge 0, i \in F_I$$

$$u_r \ge \varepsilon \ge 0, r \in C_R, r \in F_R$$

$$v_i \ge \varepsilon \ge 0, i \in C_I, i \in F_I$$

III. ILLUSTRATIVE SUPPLIER SELECTION PROBLEM

In the presented problem, each decision making unit (DMU) represents a supplier alternative. This paper uses hypothetical data for medical device supplier selection criteria that are chosen from [1]. Reliability (the percentage of defective items) and late delivery present the cost criteria which are considered as input, while the managerial capability and experience in the sector are the benefit criteria, so they are taken into account as outputs. As can be understood from the table given below, experience in the sector and reliability, which are the exact values for each alternative, are evaluated as years and percentage, respectively. On the other hand, managerial capability and late delivery are evaluated by two decision makers, equally weighted, with linguistic terms.

TABLE I
DATA FOR MEDICAL SUPPLIER SELECTION CRITERIA

Supplier alternative	Managerial capability	Experience in the sector	Reliability	Late delivery
DMU 1	VH-DH	5	2.5	M-L
DMU 2	L-L	12	3.9	M-H
DMU 3	M-H	14	2.7	VL-DL
DMU 4	H-H	13	2.6	M-M
DMU 5	M-L	10	4	M-H
DMU 6	VH-H	8	5.1	VH-H
DMU 7	M-M	17	3	M-M
DMU 8	L-VL	13	3.2	M-H

The corresponding fuzzy scale for the linguistic term set is considered as DL: (0, 0, 0.16), VL: (0, 0.16, 0.33), L: (0.16, 0.33, 0.50), M: (0.33, 0.50, 0.66), H: (0.50, 0.66, 0.83), VH: (0.66, 0.83, 1), DH: (0.83, 1, 1).

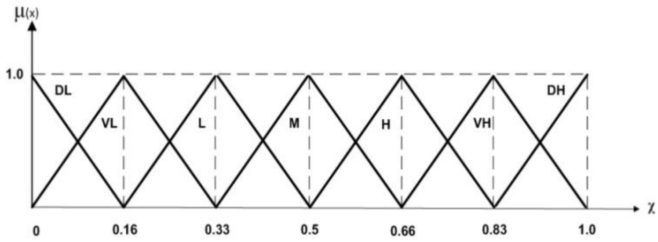

FIGURE 1
MEMBERSHIP FUNCTIONS FOR LINGUISTIC VARIABLES
(DL: (0, 0, 0.16), VL: (0, 0.16, 0.33), L: (0.16, 0.33, 0.50), M: (0.33, 0.50, 0.66), H:(0.50, 0.66, 0.83), VH: (0.66, 0.83, 1), DH: (0.83, 1, 1)).

For scaling adjustment, experience in the sector and reliability terms are normalized with max-value normalization method. Then the models that are represented above, are applied with $\varepsilon = 0.001$ and $\alpha = 0.1$. The results are as given in Table II.

TABLE II
DEA EFFICIENCY SCORES OF DMUs

Supplier alternative	Optimistic scenario efficiency score	Pessimistic scenario efficiency score
DMU 1	1	0.775
DMU 2	0.981	0.543
DMU 3	1	0.915
DMU 4	1	0.882
DMU 5	0.981	0.441
DMU 6	0.985	0.373
DMU 7	1	1
DMU 8	0.988	0.717

As is illustrated in the table given above, for the optimistic scenario, four supplier alternatives are evaluated as efficient, while for the pessimistic scenario, only DMU7 is the efficient-alternative. It is worth nothing that pessimistic model, provides a robust classification, yielding to a single-efficient DMU.

IV. CONCLUSION

In this work, the most suitable medical device supplier alternative is identified using fuzzy data envelopment analysis-based group decision making approach which provides a performance evaluation in order to improve customer satisfaction. Future research may focus on incorporating ordinal data into the decision framework.

REFERENCES

[1] E. E. Karsak, and M. Dursun, "An integrated fuzzy MCDM approach for supplier evaluation and selection", *Computers & Industrial Engineering*, vol. 82, pp. 82-93, 2015.
[2] T. Ahmad, and S. Mondal, "Dynamic supplier selection model under two-echelon supply network", *Expert Systems with Applications*, vol. 65, pp. 255-270, 2016.
[3] E. E. Karsak, and M. Dursun, "An integrated supplier selection methodology incorporating QFD and DEA with imprecise data", *Expert Systems with Applications*, vol. 41, pp. 6995-7004, 2014.
[4] A. Charnes, W. W. Cooper, and E. Rhodes, "Measuring the efficiency of decision-making units", *European Journal of Operational Research*, vol. 2, pp. 429-444, 1978.
[5] J. Doyle, and R. Green, "Efficiency and cross-efficiency in DEA: Derivations, meanings and uses", *Journal of the Operational Research Society*, vol. 45, no. 5, pp. 567-578, 1994.

[6] E. E. Karsak, and S. S. Ahiska, "Practical common weight multi-criteria decision-making approach with an improved discriminating power for technology selection", *International Journal of Production Research,* vol. 43, no. 8, pp. 1537-1554, 2005.

[7] N. Goker, and E. E. Karsak, "An improved common weight DEA-based decision approach for problems with multiple inputs and multiple outputs", *Proceedings of The 20th World Multi-Conference on Systemics, Cybernetics and Informatics,* pp. 68-73, 2016.

[8] X. B. Li, and G. R. Reeves, "A multiple criteria approach to data envelopment analysis", *European Journal of Operational Research,* vol. 115, pp. 507-517, 1999.

[9] J. K. Sengupta, "A fuzzy systems approach in data envelopment analysis", *Computers & Mathematics with Application,* pp. 259-266, 1992.

[10] L. A. Zadeh, "Fuzzy sets", *Information and Control,* pp. 338-353, 1965.

[11] L. A. Zadeh, "Fuzzy sets as a basis for a theory of possibility", *Fuzzy Sets and Systems,* pp. 3-28, 1978.

[12] K. Triantis, and O. Girod, "A mathematical programming approach for measuring technical efficiency in a fuzzy environment", *Journal of Productivity Analysis,* vol. 85-102, 1998.

[13] M. S. Saati, A. Memariani, and G. R. Jahanshahloo, "Efficiency analysis and ranking of DMUs with fuzzy data", *Fuzzy Optimization and Decision Making,* pp. 255-267, 2002.

[14] P. Guo, and G. Tanaka, "Fuzzy DEA: A perceptual evaluation method", *Fuzzy Sets and Systems,* pp. 149-160, 2001.

[15] N. Adler, L. Friedman, and Z. Sinuany-Stern, "Review of ranking methods in the data envelopment analysis context", *European Journal of Operational Research,* pp. 249-265, 2002.

[16] A. Hatami-Marbini, A. Emrouznejad, and M. Tavana, "A taxonomy and review of the fuzzy data envelopment analysis literature: Two decades in the making", *European Journal of Operational Research,* pp. 457-472, 2011.

[17] E. E. Karsak, "Using data envelopment analysis for evaluating flexible manufacturing systems in the presence of imprecise data", *International Journal of Advanced Manufacturing Technology,* vol. 35, pp. 867-874, 2008.